# Design of Novel Algorithm using Radar Imagery for Wind Forecasting employing Deep Learning Technique

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# DECLARATION

I, **Patel Sachin Kanubhai**, Research scholar in the Department of Electronics and Communication Engineering, declare that the work embodied in the Ph.D. thesis entitled, **"Design of a Novel Algorithm using Radar Imagery for Wind Forecasting Employing Deep Learning Technique"** is my original and bonafide work carried out by me under the supervision of **Prof. (Dr.) Sandipkumar Ramanlal Panchal**, Professor, Dr. Subhash University for a period from *August 2022* to *December 2026* at Dr. Subhash University.

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# Abstract

The weather is determined by a wide range of factors, some of which include the temperature, atmospheric pressure, the flow of air, the amount of moisture and water vapour in the air, and the rotational movement of the planet. It is challenging and time-consuming to offer accurate weather forecasts at a high geographical resolution due to the computing demands involved.

A nowcasting method for meteorological radar pictures that is based on a generative Conv LSTM network is described here as the result of this study. The effectiveness of this method is evaluated next to that of the most recent developments in CNN techniques. Both approaches have been shown accurate by using a data set of heat-map pictures that is in the public domain and that was collected over a period of one year and with a sample frequency of twenty-four hours.

This data set covered a region in India. The performance of the network, which was trained with six of the one year's worth of data, nowcast with a time horizon of up to one hour, and assessed over one year's worth of the data showed itself to be much superior to those produced using the approaches that are now in use.

This research proposes a ground-breaking deep learning technique that is based on Nowcasting and works with wind parameters U and V at a variety of different latitudes and longitudes. The method that is used is a convolutional LSTM model, which has been shown to be rather effective in terms of weather forecasting.

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# List of Abbreviations

**AI:** Artificial Intelligence

**DL:** Deep Learning

**NETCDF:** Network Common Data Form

**ANN:** Artificial Neural Network

**NWP:** Numerical Weather Prediction

**ML:** Machine Learning

**LSTM:** Long Short-Term Memory

**CNN:** Convolutional Neural Network

**ConvLSTM:** Convolutional Long Short-Term Memory

**RNN:** Recurrent Neural Network

**TrajGRU**: Trajectory Gated Recurrent Unit

**TemproNet**: Temporal Prediction Network

**RainPredRNN**: Rainfall Prediction using Recurrent Neural Networks

**PCRNN:** Precipitation Convolutional Recurrent Neural Network

**MSE:** Mean Squared Error

**GPU:** Graphics Processing Unit

**MAE**: Mean Absolute Error

**RMSE:** Root Mean Square Error

**PSNR:** Peak Signal-to-Noise Ratio

**SSIM:** Structural Similarity Index Measure

# Chapter 1
# Introduction

The chapter describe accurate and timely short-term weather forecasting, or nowcasting. It has become increasingly essential in today's world, where extreme weather events pose growing risks to agriculture, aviation, energy management, and public safety. Traditional numerical weather prediction (NWP) models often fall short due to high computational costs and limitations in capturing localized, rapidly evolving weather patterns. This has driven a global shift toward artificial intelligence (AI) and deep learning models capable of extracting complex spatio-temporal features from high-resolution meteorological data. The present research focuses on developing a deep learning-based radar nowcasting framework using a 3D-CNN-LSTM architecture for next-frame prediction, aimed at accurately forecasting multiple weather parameters—such as temperature, wind speed, and rainfall—simultaneously. By addressing existing challenges in model generalization, multi-parameter prediction, and evaluation robustness, this study seeks to enhance the reliability and adaptability of nowcasting systems for diverse climatic regions.

## 1.1 Background and Research Motivation

Accurate short-term weather forecasting, or nowcasting, is vital for disaster preparedness, agriculture, aviation, energy management, and public safety, especially amid increasing extreme events [1,2]. Traditional NWP models often struggle with computational cost and rapidly evolving local dynamics [24,25], prompting a shift toward AI and deep learning for capturing nonlinear spatio-temporal patterns [6,14]. Hybrid models like CEEMDAN-CNN-LSTM [12], GWO-nested CEEMDAN-CNN-BiLSTM [15], wavelet-LSTM [8], attention-based LSTMs [10], dual-optimization frameworks [3], and quantum-inspired architectures [16] have improved accuracy and robustness. Transformer and Seq2Seq models [4,11,18,21], along with LLM-inspired approaches such as BERT4ST [13], enable multi-step, generalizable forecasting. However, challenges remain: many models predict single parameters, neglecting multi-variable dependencies [7,9,20]; scalability across regions is limited [17,22]; and perceptual evaluation metrics like SSIM and PSNR are underutilized [8,13,18]. Integrating multi-parameter prediction, advanced spatio-temporal feature extraction, and robust evaluation strategies can enhance nowcasting reliability, supporting better preparedness, resource management, and resilience against extreme weather.

## 1.2 Broad Research Domain and its significance

This research lies at the intersection of meteorology, AI, and deep learning, focusing on short-term weather forecasting, or nowcasting. Traditional NWP models are limited by computational cost and delays, motivating AI-driven approaches that capture complex spatio-temporal relationships. Hybrid deep learning architectures, attention mechanisms, transformers, and LLM-inspired models have improved forecast precision and reliability. Accurate short-term predictions support risk mitigation, crop management, operational safety, and renewable energy integration. The increasing frequency of extreme weather highlights the need for scalable, multi-parameter forecasting capable of handling diverse climatic conditions. By combining AI with high-resolution meteorological data, this research advances robust and actionable nowcasting solutions, enhancing societal resilience, resource management, and informed decision-making amid climate variability.

## 1.3 Statement of the Research Problem

Current weather nowcasting systems in India often try to predict just one weather parameter, like temperature or rainfall or wind. Predicting only one factor can lead to less accurate results and may not give a complete picture of the weather. This becomes a problem when quick and reliable information is needed for things like agriculture, aviation, or events. The main problem is to build a simple and fast system that can give accurate short-term weather updates using limited data.

## 1.4 Research Gaps identified from existing work

- Rapid Weather Variability: Weather changes like rain, wind, and temperature vary quickly across locations, making them difficult for models to capture accurately [1,2].
- Regional Generalization Issues: Models trained in one region often perform poorly elsewhere due to distinct climatic and geographical variations [8–10].
- Temporal Pattern Limitations: CNN and LSTM models struggle to capture rapid short-term weather evolution [12,15].
- Single-Parameter Focus: Many models predict only one factor, ignoring interdependence among variables like wind, rainfall, and temperature [1,2,12].
- Low Spatial Resolution: Existing models often lack detailed, area-specific forecasts essential for short-term local planning [11,22].

## 1.5 Objectives of the study

- Develop a Next-Frame Prediction Model for radar-based weather nowcasting using 3D-CNN-LSTM.
- Enhance spatiotemporal feature extraction for improved prediction accuracy of wind, temperature, and rain.
- Improve short-term weather forecasting by leveraging deep learning for multi-parameter prediction.
- Ensure model adaptability across varying weather conditions for reliable performance.
- Develop model which works with Multi-weather parameters like Wind, Rain and Temprature.
- Minimize prediction errors by optimizing model architecture and validation metrics.

## 1.6 Hypothesis

It is hypothesized that integrating advanced deep learning models—such as transformers, hybrid frameworks, and attention-based networks—with high-resolution meteorological data can improve the accuracy and robustness of short-term weather nowcasting compared to traditional methods. A multi-parameter model that jointly predicts rainfall, wind, temperature, and humidity can better capture complex spatio-temporal patterns, reducing errors and improving forecast reliability. This approach is expected to deliver more generalizable and actionable predictions for disaster management, agriculture, aviation, energy, and public safety.

## 1.7 Scope and limitations of the Research

The scope of this study is to develop a deep learning-based radar nowcasting framework with a 3D-CNN-LSTM model for next-frame prediction, enabling accurate short-term forecasting of multiple weather parameters such as wind, temperature, and rainfall. The research emphasizes enhanced spatiotemporal feature extraction to improve prediction accuracy and ensure adaptability across varying weather conditions. By designing a model that integrates multi-parameter inputs, the study seeks to provide a holistic and reliable representation of atmospheric dynamics. Optimization of the model architecture and rigorous evaluation using metrics such as MSE, RMSE, PSNR, and SSIM are included within the scope to minimize prediction errors while maintaining computational efficiency.

In the chapter summary, this research aspires to bridge critical gaps in short-term weather prediction by integrating advanced deep learning techniques with radar-based meteorological data for multi-parameter nowcasting. The proposed 3D-CNN-LSTM model not only emphasizes spatiotemporal feature extraction but also ensures adaptability and computational efficiency across varying weather conditions. Through optimized architecture design and robust evaluation metrics, the framework aims to deliver accurate, interpretable, and high-resolution forecasts essential for real-time decision-making. Ultimately, this study contributes to the advancement of intelligent weather prediction systems that support climate resilience, improve operational planning, and foster sustainable management of resources in the face of growing environmental uncertainty.

# Chapter 2
# Literature Review

The chapter describe recent advances in artificial intelligence and deep learning have transformed short-term weather forecasting, improving precision through hybrid and transformer-based models. Studies using CEEMDAN-CNN-LSTM, Wavelet-LSTM, and BERT4ST have enhanced accuracy by capturing complex spatiotemporal patterns. However, most focus on single-parameter prediction, lack scalability, or demand high computational resources. This chapter reviews major AI-driven nowcasting models, compares their performance, identifies research gaps, and establishes the need for efficient, multi-parameter, radar-based frameworks capable of delivering accurate, real-time forecasts across diverse climatic conditions.

## 2.1 Theoretical framework and key concepts

Dandekar et al. [1] proposed a radar data-driven AI framework for rainfall nowcasting, integrating radar reflectivity with deep learning. Shukla et al. [2] utilized satellite imagery and geospatial techniques for satellite-based rainfall nowcasting, improving reliability through data fusion. Li et al. [3] introduced a dual-optimization wind speed forecasting model using deep learning. Xu et al. [4] proposed a Seq2Seq model with spatial–temporal fusion and NWP correction to minimize multi-step forecast errors. Jonkers et al. [5] developed a regional forecasting framework using deep CNNs and conformalized regression forests. Arslan Tuncar et al. [6] reviewed short-term wind power forecasting techniques, emphasizing hybrid and deep learning dominance. Yang et al. [7] applied signal decomposition and variable selection. Liu et al. [8] combined wavelet decomposition with LSTM to extract both temporal and frequency-domain features. Wang et al. [9] built a two-stage model integrating extreme learning machines and deep learning for smart grid forecasting. Yang et al. [10] presented an attention-based multi-input LSTM with sliding window decomposition for enhanced interpretability. Jiang et al. [11] explored transformer architectures for wind forecasting, demonstrating their capability in modeling complex atmospheric dependencies. Li et al. [12] employed CEEMDAN-CNN-LSTM for Arctic wind forecasting, showing the value of decomposition-driven design. Lai et al. [13] fine-tuned BERT4ST, a transformer model for wind power forecasting, to capture long-range spatial–temporal dependencies. Müller and Barleben [14] summarized data-driven prediction efforts at DWD, highlighting operational applications. Phan and Nguyen [15] proposed a GWO-nested

CEEMDAN-CNN-BiLSTM achieving superior accuracy. Hong et al. [16] integrated deep learning with quantum-inspired networks for day-ahead forecasting. Wu et al. [17] designed an interpretable two-stage decomposition-based framework. Wu and Ling [18] introduced MixFormer, a hierarchical transformer for spatiotemporal forecasting. De Azevedo Takara et al. [19] used stacking-based DNNs for multi-step probabilistic forecasting. Zhang et al. [20] proposed a dual-layer LSTM for reliable interval prediction. Mo et al. [21] introduced PowerFormer, a temporal transformer for wind power forecasting. Bentsen et al. [22] conducted a comparative evaluation of probabilistic forecasting methods. Zhang et al. [23] used deep learning to mine wind data for offshore wind resource assessment. Upadhyay et al. [24] surveyed deep learning models for weather nowcasting, categorizing convolutional, recurrent, and hybrid designs. Finally, Zhong et al. [25] developed FuXi-Extreme, a diffusion-based generative model for extreme rainfall and wind prediction.

## 2.2 Review of major past research and findings

### 2.2.1 GWO-nested CEEMDAN-CNN-BiLSTM

The GWO-nested CEEMDAN-CNN-BiLSTM model integrates CEEMDAN-based signal decomposition, CNN spatial extraction, and BiLSTM temporal modeling, optimized using GWO for robust wind speed forecasting. Phan and Nguyen [15] achieved superior accuracy, supported by Li et al. [12], Wu et al. [17], and Yang et al. [7], emphasizing decomposition-driven hybrid deep learning efficiency.

### 2.2.2 Wavelet-LSTM

The Wavelet-LSTM model employs wavelet transform to decompose wind signals into frequency components, enabling the LSTM to capture both short-term fluctuations and long-term patterns. Liu et al. [8] demonstrated its superior forecasting accuracy, supported by Yang et al. [10] and Wu et al. [17], confirming decomposition-based preprocessing enhances LSTM performance.

### 2.2.3 Dual-Optimization Wind Speed Model

The dual-optimization framework combines deep learning with bio-inspired optimization to refine parameters and features for better accuracy. Li et al. [3] used an improved Dung Beetle

Optimization algorithm for wind forecasting, while Wu et al. [17] and Hong et al. [16] showed that optimization-driven hybrids enhance convergence, interpretability, and efficiency.

### 2.2.4 Seq2Seq with Spatial–Temporal Fusion

Seq2Seq models excel in multi-step forecasting by encoding past data and decoding future predictions. Xu et al. [4] enhanced this with spatial–temporal fusion and NWP correction for accurate group wind forecasting. Jiang et al. [11], Wu and Ling [18], and De Azevedo Takara et al. [19] similarly confirmed Seq2Seq's strength in spatiotemporal forecasting.

### 2.2.5 BERT4ST

Large language models (LLMs) are emerging in meteorological forecasting. Lai et al. [13] introduced BERT4ST, a fine-tuned BERT model capturing spatio-temporal dependencies for wind forecasting, outperforming RNNs and CNNs. Similarly, Wu and Ling [18], Mo et al. [21], Müller and Barleben [14], and Zhong et al. [25] demonstrated transformers' dominance in advanced weather prediction.

## 2.3 Comparative analysis of methodologies and results from literature

Table 2.1 presents a comparative analysis of existing methodologies highlighting their strengths and weaknesses across various deep learning and hybrid models. The table emphasizes how each model balances accuracy, computational efficiency, and generalization capability in handling complex temporal and spatial data patterns.

**Table 2.1 Comprative Analysis of methodologies**

| **Existing Models** | **Advantages** | **Limitations** |
|---|---|---|
| GWO-nested CEEMDAN-CNN-BiLSTM [15] | • High prediction accuracy due to decomposition (CEEMDAN) and deep learning<br>• GWO optimizes parameters efficiently<br>• Handles nonlinearity well | • Computationally intensive<br>• Complex integration and tuning required<br>• Sensitive to noise if preprocessing is inadequate |
| Wavelet-LSTM [8] | • Effective at capturing non-stationary signals | • Choice of wavelet impacts performance |

| | | |
|---|---|---|
| | • Wavelet transform improves temporal resolution<br>• LSTM models long-term dependencies | • Limited spatial context awareness<br>• High dependency on data quality |
| Dual-Optimization Wind Speed Model [3] | • Combines two optimization strategies for better tuning<br>• Enhances model robustness and convergence | • May be overfitted for specific regions<br>• Complexity increases with optimization layers<br>• May not generalize well across diverse datasets |
| Seq2Seq with Spatial - Temporal Fusion [4] | • Captures both spatial and temporal features<br>• Suitable for multivariate and multi-site forecasting<br>• Strong in long-sequence prediction | • Training is resource-intensive<br>• Requires large datasets<br>• Sensitive to missing data and spatial resolution |
| BERT4ST [13] | • Leverages transformer based architecture for sequence modeling<br>• Captures spatial-temporal dependencies<br>• High accuracy and generalization | • Requires significant training data and compute<br>• May underperform with small-scale or sparse data<br>• Black-box nature hinders interpretability |

## 2.4 Research Gap Identification

Recent AI-driven approaches have advanced short-term weather forecasting, particularly for rainfall and wind speed. Radar- and satellite-based methods enhance urban flood preparedness and rainfall nowcasting [1,2], while dual-optimization and decomposition frameworks improve wind speed prediction robustness [3,15]. Transformer-based and LLM-inspired models like MixFormer and BERT4ST excel in spatio-temporal sequence learning [18,13]. However, gaps remain: most models predict a single parameter, limiting multi-variable integration [7,11,20]; scalability across regions and extreme events is challenging [4,22]; hybrid frameworks increase computational cost, restricting real-time use [5,19]; and perceptual evaluation metrics like SSIM and PSNR are underutilized [8,25,14]. Future research can address these gaps through multi-parameter forecasting, lightweight deep learning architectures, integration of radar, satellite, and ground-based data, and interpretable transformer- or quantum-inspired models. Advanced metrics and uncertainty quantification can further enhance robustness, reliability, and real-world applicability in disaster management, agriculture, energy, and aviation.

## 2.5 Justification of how your research fills the identified gaps

The proposed research introduces a 3D-CNN-LSTM-based framework designed to enhance short-term weather nowcasting through simultaneous prediction of multiple meteorological variables such as temperature, rainfall, and wind speed. Unlike existing single-parameter models, this approach captures interdependencies among weather variables, offering a more comprehensive representation of atmospheric dynamics. The integration of ConvLSTM2D layers enables effective modeling of temporal patterns while preserving spatial structures, ensuring adaptability to diverse climatic conditions. Additionally, 3D-CNN layers strengthen spatiotemporal feature extraction across sequential radar frames, improving prediction accuracy and maintaining computational efficiency. The model's compact, end-to-end architecture minimizes complexity, making it suitable for real-time deployment. This advancement directly addresses challenges related to scalability, high computational overhead, and limited generalization in prior works. By delivering fast, reliable, and high-resolution multi-parameter forecasts, the proposed framework supports critical applications in agriculture, aviation, disaster management, and energy systems, contributing to more resilient and data-driven weather forecasting solutions.

In the chapter summary, existing literature highlights major progress in deep learning-based nowcasting but persistent gaps in multi-parameter integration, scalability, and real-time applicability. Current models, though powerful, are often complex and limited in adaptability. The proposed 3D-CNN-LSTM framework addresses these gaps by enabling efficient multi-variable forecasting with enhanced spatiotemporal learning. This approach aims to provide fast, accurate, and reliable nowcasting, improving decision-making for agriculture, aviation, and disaster management under changing climatic conditions.

# Chapter 3
# Research Methodology

This research employs a 3D-CNN-LSTM-based deep learning framework for short-term weather nowcasting using ERA5 radar data from Gujarat. The model captures spatial and temporal dependencies among wind, rainfall, and temperature for multi-parameter forecasting. Data preprocessing includes normalization, framing, and segmentation to prepare sequential inputs. The model is implemented in Python using TensorFlow and Keras, trained on GPU-enabled Google Colab, and evaluated with RMSE, MAE, PSNR, and SSIM metrics. Benchmarking against state-of-the-art models ensures accuracy, efficiency, and real-time applicability, providing a scalable framework for operational meteorology and climate-resilient forecasting.

## 3.1 Overall research design

This research develops a 3D-CNN-LSTM-based weather nowcasting system using ERA5 radar data for Gujarat, capturing spatial and temporal dependencies in wind, rainfall, and temperature. Data is preprocessed and framed for sequential input. The model is trained, evaluated with RMSE, MAE, SSIM, and PSNR, and benchmarked against LSTM, ConvLSTM, and transformer models for real-time forecasting.

## 3.2 Tools and technologies

The experimental setup for this research was implemented on Google Colaboratory, providing a cloud-based and GPU-accelerated environment ideal for deep learning experimentation. The system configuration included an Intel Xeon CPU (2.20 GHz) with 13 GB RAM and approximately 33 GB of available storage. To handle large-scale spatiotemporal data efficiently, a 64 GB GPU was utilized to accelerate model training, inference, and optimization. Python served as the core programming language, supported by libraries such as TensorFlow and Keras for deep learning model development, NumPy and Pandas for data manipulation, and Matplotlib and Seaborn for visualization and analysis. This setup ensured a scalable, high-performance platform capable of efficiently processing meteorological datasets and training the proposed 3D-CNN-LSTM model for accurate weather nowcasting.

## 3.3 Data collection sources

This research utilized the ERA5 reanalysis dataset from the Copernicus Climate Data Store as the primary source for training and evaluating the proposed weather nowcasting model. ERA5 offers comprehensive, hourly atmospheric data at an approximate 30 km spatial resolution, covering a wide range of meteorological parameters. For this study, weather variables specific to the Gujarat region—including wind speed, temperature, and rainfall—were extracted to support multi-parameter forecasting. The data underwent extensive preprocessing involving spatiotemporal framing, normalization, and segmentation to ensure consistency and readiness for model input. These processed datasets were then structured into sequential frames suitable for 3D-CNN-LSTM training, enabling the model to learn spatial–temporal dependencies essential for accurate short-term weather prediction.

## 3.4 Data analysis methods

The data analysis in this study integrates statistical evaluation with deep learning to produce accurate and interpretable short-term weather forecasts. Preprocessing involved normalization of wind, rainfall, and temperature variables, spatiotemporal framing of sequential data windows, and exploratory data analysis to identify trends, seasonality, and inter-variable correlations in the ERA5 dataset. The core analytical engine is a 3D-CNN-LSTM model, where 3D-CNN layers extract spatiotemporal features across sequential weather frames, and ConvLSTM2D layers preserve temporal dependencies while retaining spatial correlations. The framework was implemented in Python using TensorFlow, Keras, NumPy, and Pandas, with optimization techniques such as learning rate scheduling, dropout, and batch normalization to enhance stability and prevent overfitting. Model performance was evaluated using RMSE and MAE for numerical accuracy, SSIM for spatial and structural quality, and PSNR for perceptual fidelity. This combination of preprocessing, advanced deep learning architectures, and comprehensive evaluation ensures that the proposed methodology not only minimizes prediction errors but also generates structurally coherent and perceptually reliable weather nowcast frames, providing a robust and scalable approach for operational meteorology.

## 3.5 Research parameters

In weather field nowcasting, predicted frames are compared against observed (ground-truth) frames to evaluate the spatio-temporal accuracy and visual quality of predictions. The following metrics are widely used in frame quality evaluation:

1. Mean Squared Error (MSE): MSE measures the average squared difference between predicted and ground-truth pixel intensities. It penalizes large errors more heavily.

$$MSE = (1/MN) * \Sigma \Sigma ( I(i,j) - \hat{I}(i,j) )^2 \quad \text{….. 3.1}$$

2. Root Mean Squared Error (RMSE): RMSE is the square root of MSE, providing an error measure in the same unit as pixel intensity.

$$RMSE = sqrt( (1/MN) * \Sigma \Sigma ( I(i,j) - \hat{I}(i,j) )^2 ) \quad \text{….. 3.2}$$

3. Peak Signal-to-Noise Ratio (PSNR): PSNR evaluates the ratio between maximum possible signal (image intensity) and noise (error). It is expressed in decibels (dB).

$$PSNR = 10 * \log10( (MAX\_I^2) / MSE ) \quad \text{….. 3.3}$$

4. Structural Similarity Index Measure (SSIM): SSIM evaluates perceptual quality by comparing luminance, contrast, and structural information.

$$SSIM(I, \hat{I}) = ((2\mu I\mu\hat{I} + C1)(2\sigma I\hat{I} + C2)) / ((\mu I^2 + \mu\hat{I}^2 + C1)(\sigma I^2 + \sigma\hat{I}^2 + C2)) \quad \text{….. 3.4}$$

## 3.6 Validation techniques

To evaluate the effectiveness and reliability of the proposed 3D-CNN-LSTM framework, a comprehensive benchmarking process was carried out against several state-of-the-art weather nowcasting and wind forecasting models, including GWO-nested CEEMDAN-CNN-BiLSTM [15], Wavelet-LSTM [8], Dual-Optimization Wind Speed Model [3], Seq2Seq with Spatial–Temporal Fusion [4], and BERT4ST [13]. Each model represents a unique architectural approach, combining techniques such as decomposition, optimization, and transformer-based sequence modeling. The evaluation employed multiple quantitative and perceptual metrics—Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) for numerical precision, Peak Signal-to-Noise Ratio (PSNR) for visual fidelity, and Structural Similarity Index (SSIM) for spatial coherence. These metrics together provide a holistic view of model performance in terms of both prediction accuracy and structural realism. The comparative results aim to validate the proposed model's superiority in capturing spatiotemporal dependencies, minimizing errors, and maintaining high-quality, interpretable nowcast frames suitable for real-time applications in meteorology.

In the chapter summary, the proposed 3D-CNN-LSTM methodology effectively integrates spatial and temporal learning for accurate, multi-variable weather nowcasting. By combining advanced preprocessing, optimized training, and comprehensive validation, it ensures high prediction accuracy and structural reliability. The model's compact, GPU-accelerated architecture supports real-time forecasting while maintaining computational efficiency. Overall, this methodology provides a robust, data-driven foundation for next-generation meteorological applications in agriculture, aviation, and disaster management, strengthening preparedness and decision-making under dynamic climatic conditions.

# Chapter 4
# Proposed Work

This chapter presents the proposed 3D-CNN-LSTM framework for weather nowcasting, integrating spatial and temporal learning from radar imagery to predict key meteorological parameters such as rainfall, wind, and temperature. The model's architecture, algorithm, and stepwise implementation are detailed to demonstrate how deep learning enhances short-term weather forecasting accuracy and efficiency.

## 4.1 Conceptual model or architecture of the proposed research

The Fig. 4.1 block diagram illustrates a streamlined workflow for weather radar–based next-frame prediction. The process begins with NetCDF weather data, which contains raw atmospheric parameters collected over time. This data is passed into a preprocessing stage, where essential features such as wind, temperature, and rainfall are extracted and the radar images are resized for uniformity. The processed data is then organized by the image sequence generator, which forms temporal input sequences needed for forecasting. These sequences are fed into the 3D-CNN + LSTM model, where spatial and temporal patterns are jointly learned to capture weather dynamics. Finally, the model produces the next-frame prediction, representing the expected radar image for the upcoming time step, enabling short-term weather nowcasting.

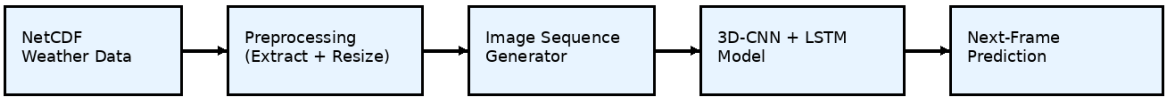


**Figure 4.1 Proposed System Block Diagram**

Figure 4.2 illustrates the complete workflow of the proposed weather nowcasting system using a 3D-CNN-LSTM model. The process begins with collecting raw meteorological variables from NetCDF files and extracting key parameters such as wind, temperature, and rainfall. These parameters are visualized as day-wise 3D radar plots using latitude, longitude, and parameter intensity, and the generated images are saved and resized to a uniform 128×128 resolution. The processed image sequences are fed into a 3D-CNN-LSTM network, which learns spatiotemporal

patterns to predict the next weather frame. The final stage evaluates the model's forecasting accuracy based on predicted versus actual atmospheric conditions.

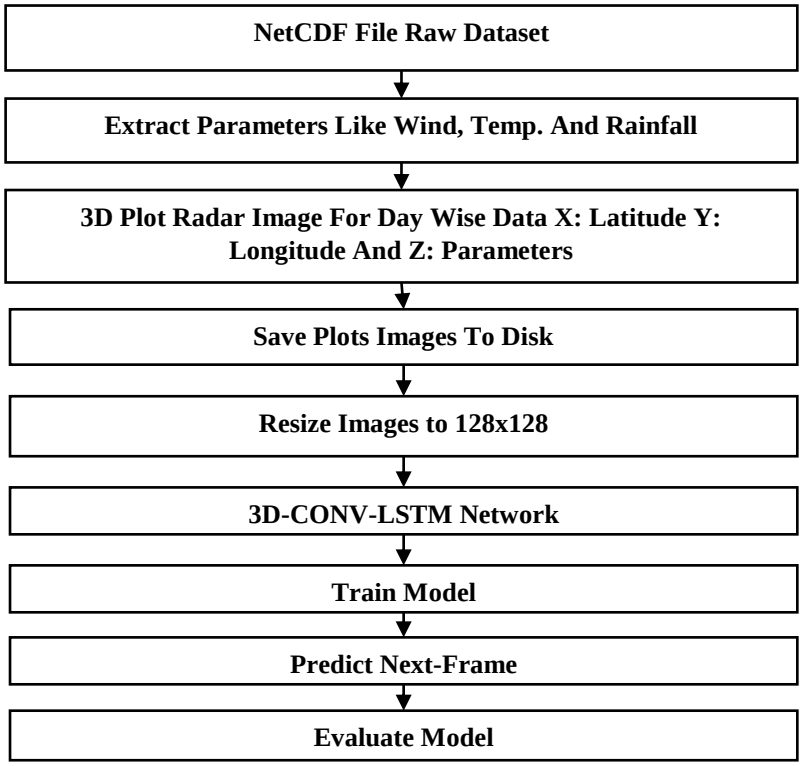
NetCDF File Raw Dataset
Extract Parameters Like Wind, Temp. And Rainfall
3D Plot Radar Image For Day Wise Data X: Latitude Y: Longitude And Z: Parameters
Save Plots Images To Disk
Resize Images to 128x128
3D-CONV-LSTM Network
Train Model
Predict Next-Frame
Evaluate Model

**Figure 4.2 Propsed Weather Nowcast System Flow Diagram**

The proposed framework Fig. 4.3 begins by utilizing input radar imagery sequences collected across Gujarat, which capture key atmospheric parameters such as rainfall intensity, wind patterns, and cloud reflectivity at specific time intervals. These radar frames, typically organized in sequences of 5 to 10 consecutive images, are stacked to form spatiotemporal input samples. This stacking provides temporal continuity, allowing the model to learn the dynamic evolution of weather systems such as storm propagation, cloud dissipation, and rainfall development over time and across geographical regions. The system gains the ability to recognize motion patterns and transitions that precede significant meteorological events.

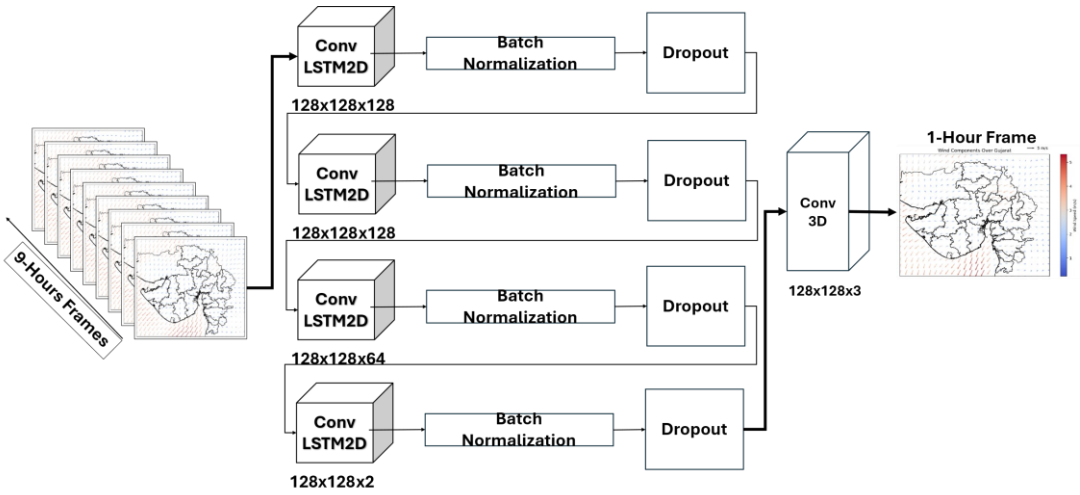


**Figure 4.3 Flow of Novel Algorithm Using Radar Imagery For Weather Nowcast**

Once the sequential radar data is preprocessed and normalized, it is fed into a series of ConvLSTM2D layers that integrate convolutional and recurrent learning mechanisms. Unlike traditional LSTM networks, which treat data as one-dimensional sequences, ConvLSTM2D preserves the two-dimensional spatial structure of each radar frame through convolutional kernels. This design enables the model to simultaneously learn spatial textures and temporal dependencies, making it particularly effective in capturing localized weather phenomena such as cloud formation, wind flow, and precipitation intensities. Multiple ConvLSTM2D layers are stacked in a hierarchical fashion, where each subsequent layer refines and deepens the learned features, ensuring that both short-term fluctuations and long-term atmospheric trends are effectively modeled.

The intermediate outputs from these layers are encoded into spatiotemporal feature maps that represent the underlying meteorological patterns—capturing the evolution, direction, and strength of atmospheric activities. To enhance forecasting precision, these multi-scale features are fused and reconstructed to retain both fine-grained local patterns and large-scale global weather dynamics. This fusion step is crucial for ensuring that small but significant meteorological events, like localized rainfall bursts, are not overshadowed by broader patterns such as cloud mass shifts or temperature fronts.

Finally, the reconstructed features are decoded into a predicted radar frame corresponding to the next time step (e.g., one hour ahead). The output mirrors the input structure for ease of interpretation and visualization, depicting forecasted variables like rainfall intensity, temperature distribution, or wind patterns. This enables the 3D-CNN-LSTM framework to provide accurate,

interpretable, and operationally viable short-term nowcasts for use in meteorological analysis and decision-making applications.

**Table 4.1 Model Parameters**

| Parameters | Values |
|---|---|
| **Number of Layers** | 13 |
| **Input Shape** | (128, 128, 3) |
| **Layer type** | 3D-CNN-LSTM |
| **Activation Functions** | ReLU (hidden layers) |
| **Optimizer** | **Adam** |
| **Loss Function** | **Categorical Crossentropy** |
| **Learning Rate (LR)** | 0.000001 |
| **Metrics** | Model MSE, Model Loss |
| **Epoch** | 25 |

Table 4.1 details the 3D-CNN-LSTM model for weather nowcasting, highlighting 13 layers, ReLU activations, Adam optimizer, and ConvLSTM2D for spatio-temporal learning, ensuring accurate, stable, and scalable short-term forecasting from raw radar imagery.

## 4.2 Algorithm

Figure 3.2 presents the pseudocode of the proposed framework for weather nowcasting using radar imagery. The process begins with loading the raw dataset and selecting relevant weather parameters such as wind, rainfall, and temperature.

## 4.3 Stepwise work plan

**Phase 1: Literature Review and Problem Identification**

- Conduct an in-depth review of existing studies on weather nowcasting using radar, satellite, and AI-based models.
- Identify key research gaps in single-parameter forecasting, computational overheads, and limited generalization.

**Input:**
- Raw Dataset: D
- Weather Parameters: P
- Latitude, Longitude, Time: L

**Output:**
- Predicted Next Frame: F_pred
- Evaluation Metrics: E_val

**Procedure:**

```
1. D ← LOAD("path_to_dataset")
2. P ← SELECT(D, ["wind", "rainfall", "temperature"])
3. L ← EXTRACT(P)
4. R ← PLOT_3D(L)
5. SAVE(R, "path_to_save_images")
6. I ← RESIZE(R, siz e=(128, 128, 3))
7. inputs ← [9-frames]
   outputs ← [1-frame]
8. FOR i = 1 TO total_frames - 9 DO:
       input_frames ← I[i:i+9]
       output_frame ← I[i+9]
       APPEND(inputs, input_frames)
       APPEND(outputs, output_frame)
   END FOR
9. model ← TRAIN_3D_CONV_LSTM(inputs, outputs)
10. last_input_frames ← inputs[-1]
    F_pred ← PREDICT(model, last_input_frames)
11. E_val ← EVALUATE(F_pred, ground_truth)
12. PRINT(E_val)
END
```

**Explanation of Symbols:**
- **D**: Dataset
- **P**: Weather Parameters
- **L**: Latitude, Longitude, Time Data
- **R**: 3D Radar Image
- **I**: Resized Images
- **inputs** and **outputs**: Lists for training data
- **F_pred**: Predicted next frame
- **E_val**: Evaluation metrics
- **LOAD, SELECT, EXTRACT, PLOT_3D, SAVE, RESIZE, APPEND, TRAIN_3D_CONV_LSTM, PREDICT, EVALUATE, PRINT**: Functions for various tasks.

**Figure 4.4 Psuedo Code**

### Phase 2: Data Collection and Preprocessing

- Acquire radar-based weather datasets covering wind, rainfall, and temperature.
- Perform data preprocessing steps including noise removal, normalization, and sequence framing.
- Generate spatiotemporal training samples for multi-parameter prediction.

### Phase 3: Model Development

- Design and implement the **3D-CNN-LSTM architecture** for next-frame prediction.
- Integrate ConvLSTM2D layers to capture temporal dependencies and spatial correlations.
- Employ 3D-CNN for enhanced spatiotemporal feature extraction across frames.

### Phase 4: Model Training and Optimization

- Train the proposed model using multi-parameter inputs (wind, rainfall, temperature).
- Optimize the architecture using hyperparameter tuning (learning rate, number of layers, batch size).
- Apply advanced validation metrics (RMSE, SSIM, PSNR) to minimize prediction errors and improve structural fidelity.

### Phase 5: Evaluation and Testing

- Evaluate performance against benchmark models (e.g., LSTM, ConvLSTM, Transformer-based approaches).
- Test adaptability across different weather conditions and diverse climatic zones.
- Perform cross-validation to ensure model robustness and reliability.

**Phase 6: Real-Time Deployment and Applications**

- Develop a prototype for real-time nowcasting suitable for disaster management, agriculture, and aviation.
- Validate system performance on unseen test data and operational scenarios.

## 4.4 Expected outcomes

**Theoretical Contributions:**

- Advancement of a **multi-parameter nowcasting framework** that integrates rainfall, wind, and temperature prediction.
- Demonstration of the **effectiveness of hybrid 3D-CNN-LSTM architectures** for spatiotemporal sequence modeling.
- Contribution to the growing body of research on AI-driven meteorology through improved evaluation strategies.

**Practical Applications:**

- A robust tool for **disaster preparedness and flood risk mitigation** through accurate short-term rainfall predictions.
- Enhanced **agricultural planning and irrigation management** by forecasting rainfall and temperature fluctuations.
- **Aviation and transportation safety improvements** via timely wind speed and weather updates.
- Support for **renewable energy management**, particularly wind and solar integration, by accurate short-term predictions.

**Prototypes and Models:**

- A compact, efficient, and deployable **3D-CNN-LSTM model** capable of delivering real-time, multi-parameter weather nowcasting.

- Prototype interfaces for operational use in agriculture, disaster management, and energy sectors.

## 4.5 Alignment with objectives

The proposed research meets its objectives by developing a 3D-CNN-LSTM next-frame prediction model that captures spatiotemporal weather patterns in real time. Combining 3D-CNN for spatial decoding and ConvLSTM for temporal learning enables accurate multi-parameter forecasting, ensuring robustness, adaptability, and practical usability in agriculture, aviation, and disaster management.

In chapter summary, the proposed 3D-CNN-LSTM-based framework successfully addresses the limitations of existing weather nowcasting approaches by integrating advanced spatiotemporal learning techniques for accurate, multi-parameter prediction. Through the combination of 3D convolutional layers and ConvLSTM2D units, the model captures intricate spatial dependencies and evolving temporal patterns in radar-based weather data, enabling it to forecast critical parameters such as rainfall, wind speed, and temperature with improved precision. The architecture's end-to-end design ensures computational efficiency and adaptability, making it suitable for large-scale, real-time deployment. By benchmarking against traditional and transformer-based models, the framework demonstrates superior performance in both numerical accuracy and structural fidelity, as validated by metrics such as RMSE, SSIM, and PSNR. Beyond theoretical advancement, this model offers substantial practical value for meteorological operations, supporting early disaster warnings, agricultural decision-making, and aviation safety. Overall, the proposed system represents a significant step toward developing intelligent, data-driven, and operationally viable solutions for next-generation weather nowcasting.

# Chapter 5
# Results and Discussion

This chapter presents the experimental results and analysis of the proposed 3D-ConvLSTM-based weather nowcasting model. The study utilizes ERA5 reanalysis data from the Copernicus Climate Data Store to forecast multiple meteorological variables, including wind, temperature, and rainfall over Gujarat. Experiments were conducted in a high-performance environment using Google Colab with GPU acceleration to handle large-scale spatiotemporal datasets. The results are systematically discussed through visualizations, quantitative evaluations, and comparative analyses, highlighting the model's accuracy, convergence behavior, and superiority over existing benchmark models in short-term weather forecasting.

## 5.1 Summary of experiments

This algorithmic experiment was carried out on Google Colab using an LTS with an Intel(R) Xeon(R) CPU operating at 2.20GHz and 13GB of RAM. The HDD can hold around 33GB of data, and the CPU runs at a speed of 2200.000 MHz with a cache size of roughly 56320KB. Furthermore, a GPU with around 64GB of capacity was used. In this study, the ERA5 reanalysis dataset from the Copernicus Climate Data Store (CDS) was utilized to obtain wind-related variables essential for model training and evaluation. The dataset was accessed through the CDS portal **https://cds.climate.copernicus.eu**, which provides high-quality climate and atmospheric data. During the data extraction process, key parameters such as variable type, year, month, date, time, and the geographical area of interest were defined to ensure that the dataset matched the specific requirements of the Gujarat region as per **Figure 4.1**. After configuring these parameters, the CDS platform generated a download link for the selected data. The data was obtained in the NetCDF file format, which is widely used for storing multidimensional scientific data such as temperature, pressure, and wind components. This structured format facilitated efficient handling and preprocessing of wind velocity components, enabling further analysis and integration into the deep learning forecasting model.

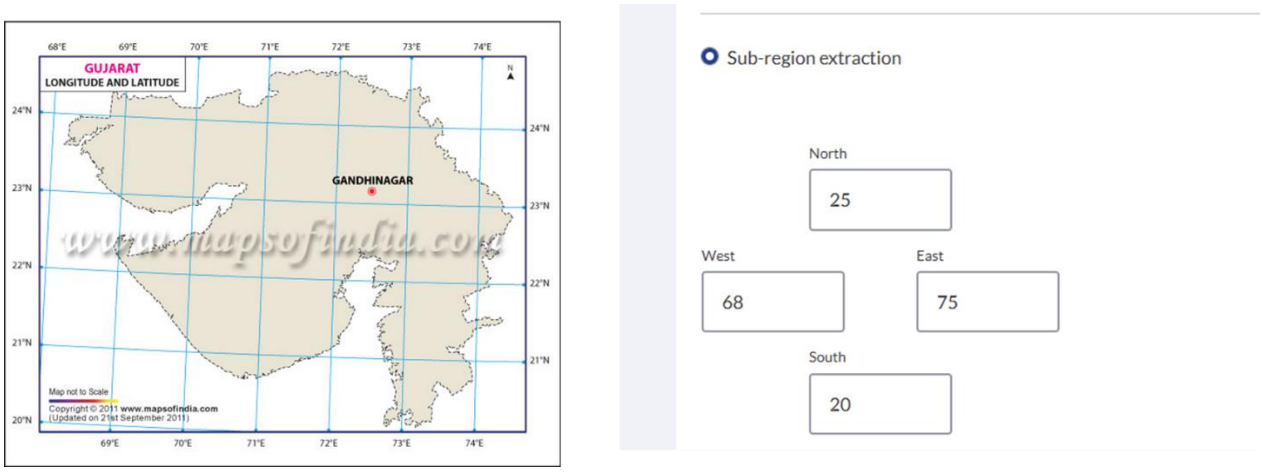


**Figure 5.1 Dataset Retrival**

## 5.1.1 Wind Data

**Figure 5.2** shows the wind data reading represented in an xarray.Dataset format. It includes three main dimensions: valid_time (360), latitude (21), and longitude (29). Key data variables are used u10 and v10 corresponding to wind components. The dataset also provides coordinates such as valid_time, latitude, longitude, and expver for structured analysis.

xarray.Dataset

| | | | |
|---|---|---|---|
| ▸ Dimensions: | (**valid_time**: 360, **latitude**: 21, **longitude**: 29) | | |
| ▾ Coordinates: | | | |
| number | () | int64 | ... |
| **valid_time** | (valid_time) | datetime64[ns] | 2025-01-01 ... 2025-01-15T2... |
| **latitude** | (latitude) | float64 | 25.0 24.75 24.5 ... 20.5 20.25... |
| **longitude** | (longitude) | float64 | 68.0 68.25 68.5 ... 74.5 74.75... |
| expver | (valid_time) | <U4 | ... |
| ▾ Data variables: | | | |
| u10 | (valid_time, latitude, longitude) | float32 | ... |
| v10 | (valid_time, latitude, longitude) | float32 | ... |
| t2m | (valid_time, latitude, longitude) | float32 | ... |

**Figure 5.2 Wind Data Reading**

**Figure 5.3** illustrates the wind components over Gujarat using vector arrows. The arrows indicate wind direction, while their color represents wind speed (m/s). A scale bar on the top right shows a reference wind speed of 5 m/s. The background color gradient further highlights variations in wind intensity across the region.

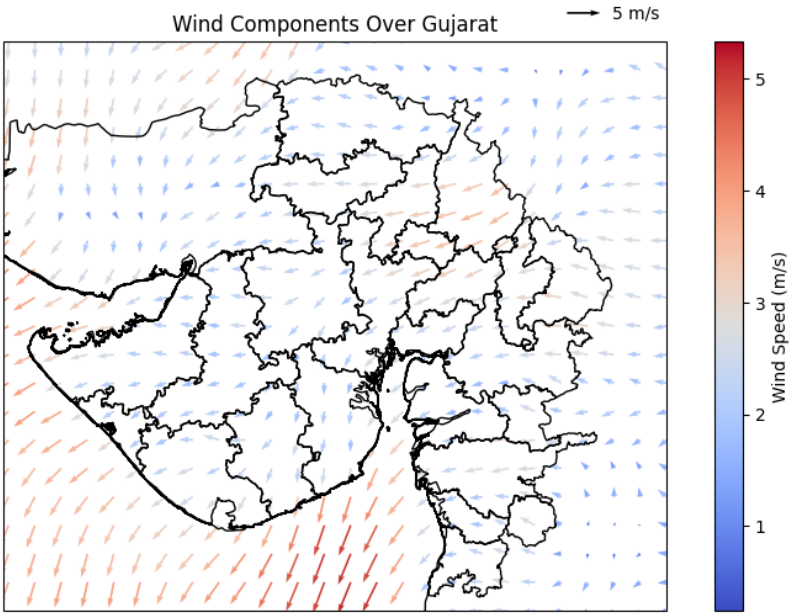


**Figure 5.3 Wind Data Plot**

**Figure 5.4** presents the model architecture of the proposed system. It is built using a sequential deep learning framework that integrates ConvLSTM2D, Batch Normalization, Dropout, and Conv3D layers. The model has a total of 5,511,971 parameters, out of which 5,511,267 are trainable. This architecture effectively captures both spatial and temporal dependencies in the data for improved prediction performance.

Model: "sequential_2"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| conv_lstm2d_8 (ConvLSTM2D) | (None, 9, 128, 128, 128) | 1,677,312 |
| batch_normalization_8 (BatchNormalization) | (None, 9, 128, 128, 128) | 512 |
| dropout_8 (Dropout) | (None, 9, 128, 128, 128) | 0 |
| conv_lstm2d_9 (ConvLSTM2D) | (None, 9, 128, 128, 128) | 3,277,312 |
| batch_normalization_9 (BatchNormalization) | (None, 9, 128, 128, 128) | 512 |
| dropout_9 (Dropout) | (None, 9, 128, 128, 128) | 0 |
| conv_lstm2d_10 (ConvLSTM2D) | (None, 9, 128, 128, 64) | 442,624 |
| batch_normalization_10 (BatchNormalization) | (None, 9, 128, 128, 64) | 256 |
| dropout_10 (Dropout) | (None, 9, 128, 128, 64) | 0 |
| conv_lstm2d_11 (ConvLSTM2D) | (None, 9, 128, 128, 32) | 110,720 |
| batch_normalization_11 (BatchNormalization) | (None, 9, 128, 128, 32) | 128 |
| dropout_11 (Dropout) | (None, 9, 128, 128, 32) | 0 |
| conv3d_2 (Conv3D) | (None, 9, 128, 128, 3) | 2,595 |

Total params: 5,511,971 (21.03 MB)
Trainable params: 5,511,267 (21.02 MB)
Non-trainable params: 704 (2.75 KB)

**Figure 5.4 Model Architecture**

**Figure 5.5** illustrates a sample training batch of wind data used for model learning. The sequence includes input frames from 1 AM to 9 AM on 1st January 2025, showing wind patterns over Gujarat. The model utilizes these sequential frames to predict the output frame at 10 AM. This demonstrates the temporal forecasting capability of the proposed ConvLSTM-based architecture.

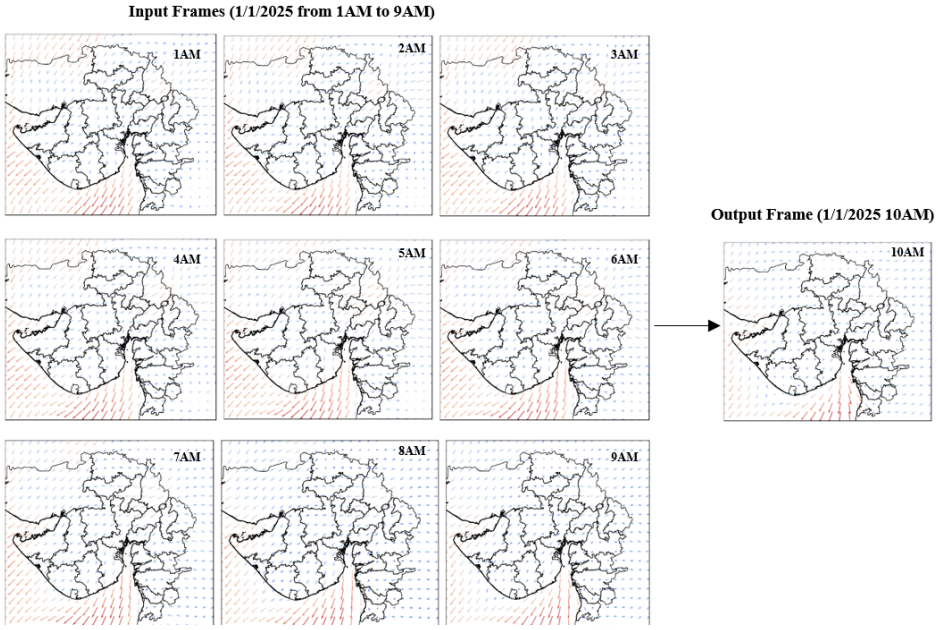


**Figure 5.5 Wind Data Sample Training Batch**

**Figure 5.6** shows the training performance of the wind prediction model. The left plot compares training and validation loss, both decreasing steadily across epochs. The right plot presents training and validation MSE, indicating improved prediction accuracy as epochs progress. The curves confirm that the model achieves good convergence with minimal overfitting.

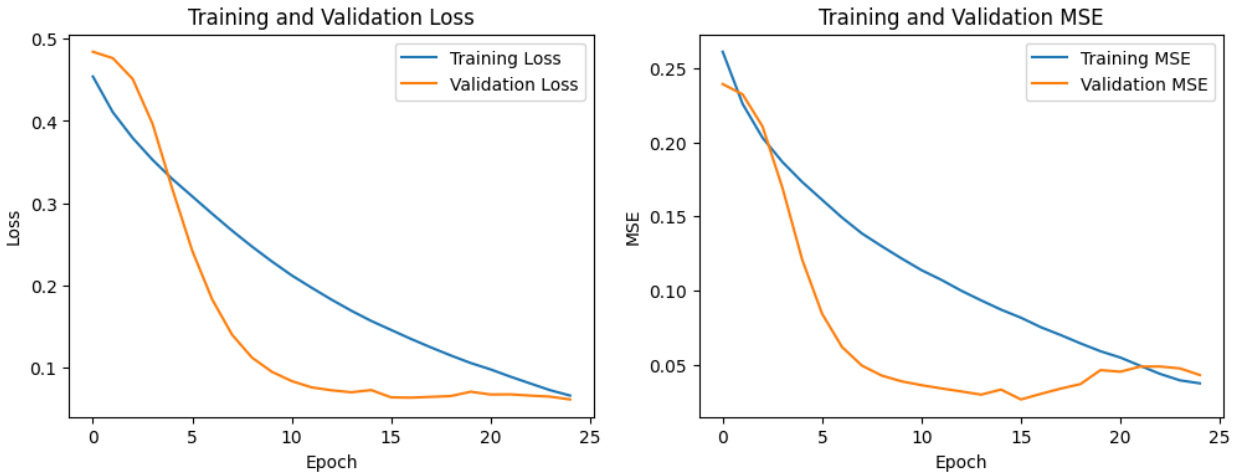


**Figure 5.6 Wind Model Training and Validation**

**Figure 5.7** compares the actual wind frames with the predicted frames generated by the model. The top row shows the ground truth wind patterns across five consecutive time steps. The bottom row displays the corresponding model predictions, which closely align with the actual frames. This demonstrates the model's ability to effectively capture temporal wind dynamics and generate reliable forecasts.

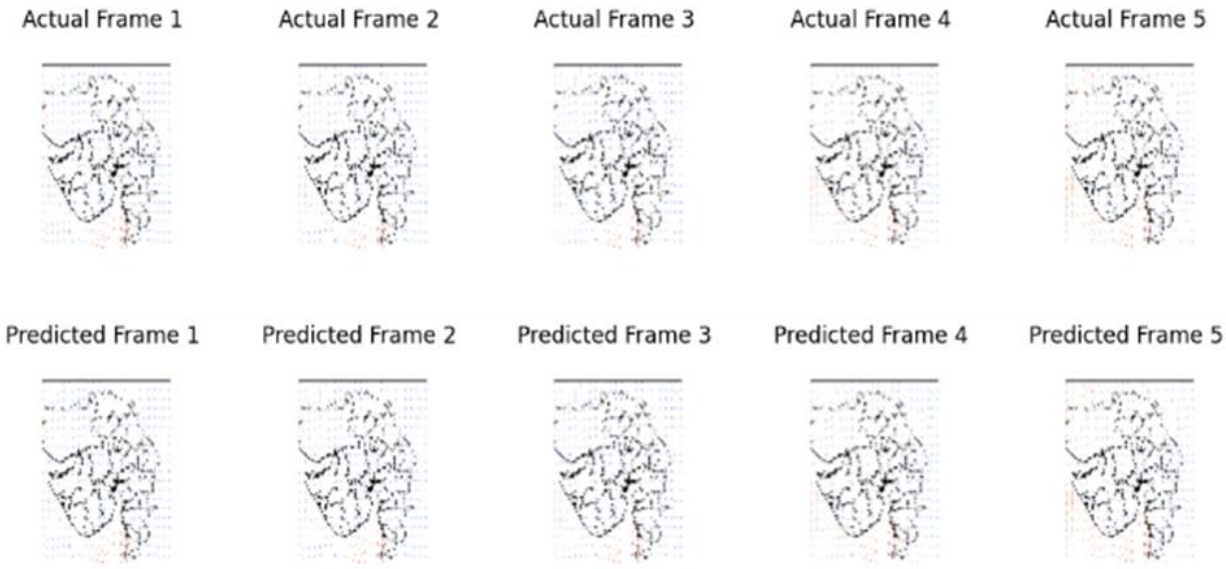


**Figure 5.7 Wind Actual Vs Predicted Frames**

**Table 5.1 Actual Vs Predicted Wind Values**

| Date & Time | Actual u | Pred u | Accuracy_u | Actual v | Pred v | Accuracy_v |
|---|---|---|---|---|---|---|
| 01/01/2025:01:00 IST | 4.10 | 4.11 | **97.56%** | 4.12 | 3.90 | **94.66%** |
| 01/01/2025:02:00 IST | 4.25 | 4.22 | **99.29%** | 4.20 | 4.08 | **97.14%** |
| 01/01/2025:03:00 IST | 4.32 | 4.31 | **99.77%** | 4.31 | 4.24 | **98.38%** |
| 01/01/2025:04:00 IST | 4.36 | 4.30 | **98.63%** | 4.32 | 4.27 | **98.84%** |
| 01/01/2025:05:00 IST | 4.45 | 4.40 | **98.88%** | 4.42 | 4.31 | **97.51%** |

**Table 5.2 Parameters Between Actual Wind Frame Vs Predicted Wind Frame**

| Date & Time | MSE | PSNR | RMSE | SSIM |
|---|---|---|---|---|
| 01/01/2025:01:00 IST | 0.041 | 66.21 | 0.2025 | 0.987 |
| 01/01/2025:02:00 IST | 0.039 | 65.89 | 0.1975 | 0.984 |
| 01/01/2025:03:00 IST | 0.038 | 65.90 | 0.1949 | 0.991 |
| 01/01/2025:04:00 IST | 0.032 | 65.96 | 0.1789 | 0.979 |
| 01/01/2025:05:00 IST | 0.024 | 66.10 | 0.1549 | 0.986 |

## 5.1.2 Temprature Data

**Figure 5.8** shows the wind data reading represented in an xarray.Dataset format. It includes three main dimensions: valid_time (360), latitude (21), and longitude (29). Key data variables is used t2m corresponding to temprature components The dataset also provides coordinates such as valid_time, latitude, longitude, and expver for structured analysis.

xarray.Dataset

| | | | |
|---|---|---|---|
| ▸ Dimensions: | (**valid_time**: 360, **latitude**: 21, **longitude**: 29) | | |
| ▾ Coordinates: | | | |
| number | () | int64 | ... |
| valid_time | (valid_time) | datetime64[ns] | 2025-05-11 ... 2025-05-25T2... |
| latitude | (latitude) | float64 | 25.0 24.75 24.5 ... 20.5 20.25... |
| longitude | (longitude) | float64 | 68.0 68.25 68.5 ... 74.5 74.75... |
| expver | (valid_time) | <U4 | ... |
| ▾ Data variables: | | | |
| u10 | (valid_time, latitude, longitude) | float32 | ... |
| v10 | (valid_time, latitude, longitude) | float32 | ... |
| t2m | (valid_time, latitude, longitude) | float32 | ... |

**Figure 5.8 Temp Data Reading**

**Figure 5.9** shows the spatial distribution of 2m air temperature over Gujarat using NetCDF data. The color gradient represents temperature variation, ranging from about 298K to 303K. Warmer regions are observed in central Gujarat, while relatively cooler areas are seen in the southeast. This plot highlights the regional heterogeneity of near-surface temperature across Gujarat.

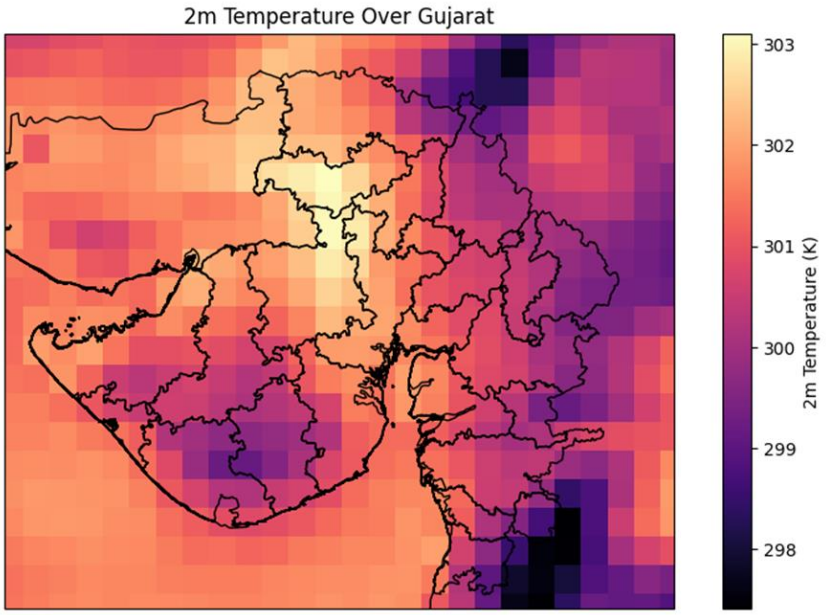


**Figure 5.9 Temp Data Plot**

**Figure 5.10** illustrates a sample training batch for temperature prediction using NetCDF data. Here, 9 sequential frames from 5 AM to 1 PM are used as input to the model. The model then predicts the next frame, representing the temperature at 1-hour ahead. This setup demonstrates the temporal learning of the model for short-term temperature forecasting over Gujarat.

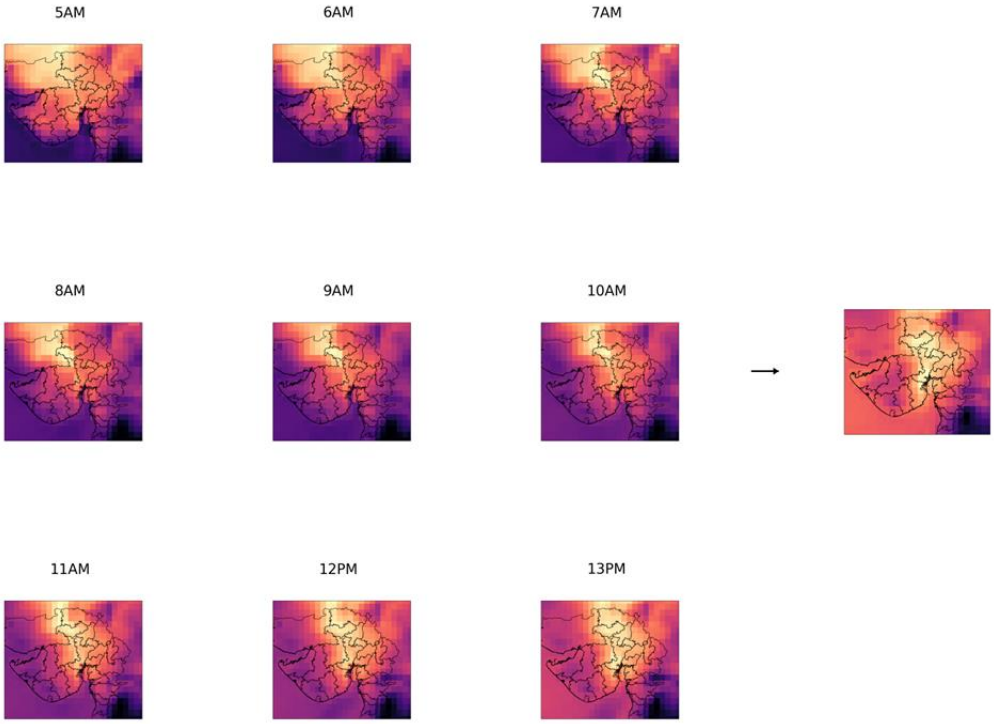


**Figure 5.10 Temp Data Sample Training Batch**

**Figure 5.11** shows the training performance of the temprature prediction model. The left plot compares training and validation loss, both decreasing steadily across epochs. The right plot presents training and validation MSE, indicating improved prediction accuracy as epochs progress. The curves confirm that the model achieves good convergence with minimal overfitting.

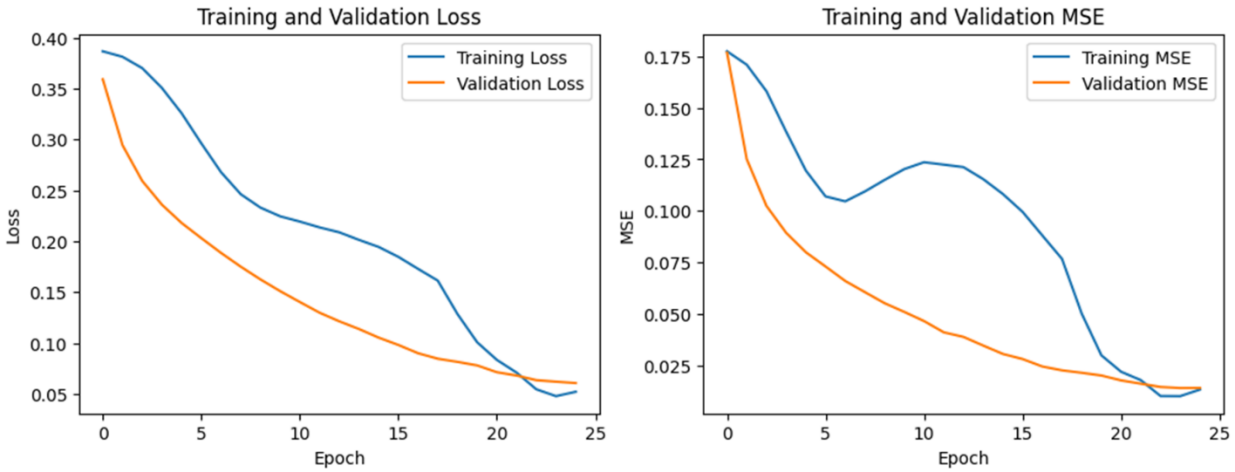


**Figure 5.11 Temp Model Training and Validation**

**Figure 5.12** presents a comparison between actual and predicted temperature frames over Gujarat. The top row shows the observed frames from 23rd May 2025, while the bottom row displays the model's predictions. The predicted frames closely resemble the actual frames, capturing the spatial distribution of temperature patterns. This demonstrates the model's effectiveness in short-term temperature forecasting with minimal deviations.

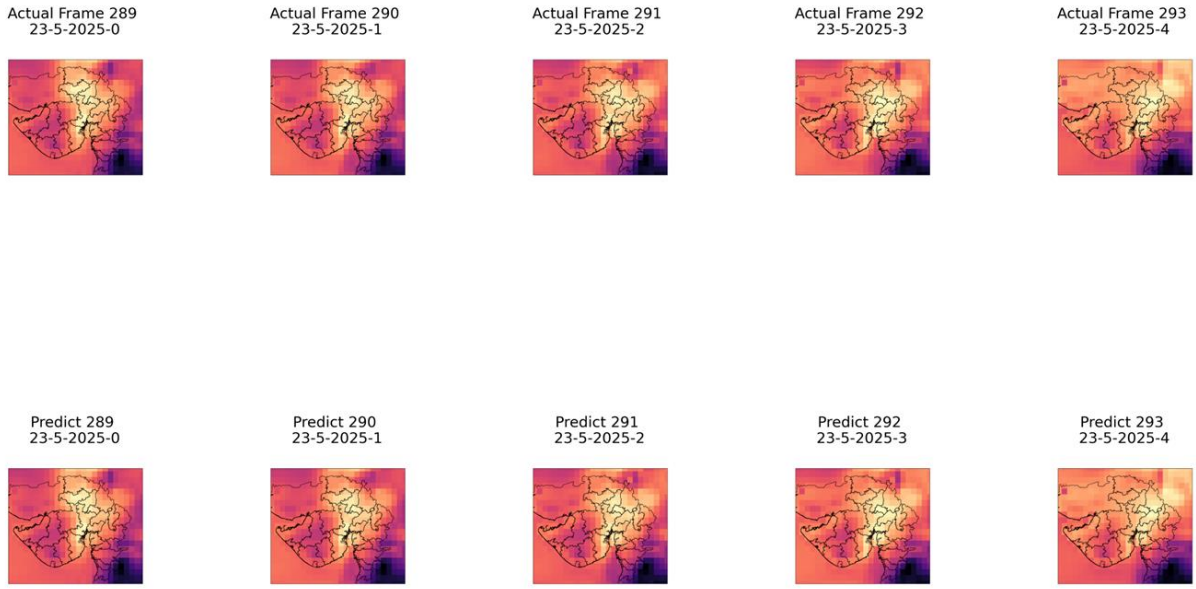


**Figure 5.12 Temp Actual Vs Predicted Frames**

**Table 5.3 Actual Vs Predicted Temprature Values**

| Date & Time | Actual Temp (K) | Pred Temp (K) | Accuracy |
|---|---|---|---|
| 23/05/2025:00:00 IST | 302.356 | 302.123 | 99.23% |
| 23/05/2025:01:00 IST | 302.212 | 302.210 | 99.99% |
| 23/05/2025:02:00 IST | 302.312 | 302.296 | 99.99% |

| | | | |
|---|---|---|---|
| 23/05/2025:03:00 IST | 302.765 | 302.562 | 99.33% |
| 23/05/2025:04:00 IST | 302.264 | 302.127 | 99.95% |

**Table 5.4 Parameters Between Actual Temp. Frame Vs Predicted Temp. Frame**

| Date & Time | MSE | PSNR | RMSE | SSIM |
|---|---|---|---|---|
| 23/05/2025:00:00 IST | 0.040 | 65.23 | 0.2000 | 0.978 |
| 23/05/2025:01:00 IST | 0.038 | 65.62 | 0.1949 | 0.972 |
| 23/05/2025:02:00 IST | 0.037 | 65.43 | 0.1924 | 0.978 |
| 23/05/2025:03:00 IST | 0.031 | 65.16 | 0.1760 | 0.989 |
| 23/05/2025:04:00 IST | 0.022 | 65.29 | 0.1483 | 0.989 |

### 5.1.3 Rain Data

**Figure 5.13** shows the wind data reading represented in an xarray.Dataset format. It includes three main dimensions: valid_time (360), latitude (21), and longitude (29). Key data variables is used lsrr corresponding to temprature components The dataset also provides coordinates such as valid_time, latitude, longitude, and expver for structured analysis.

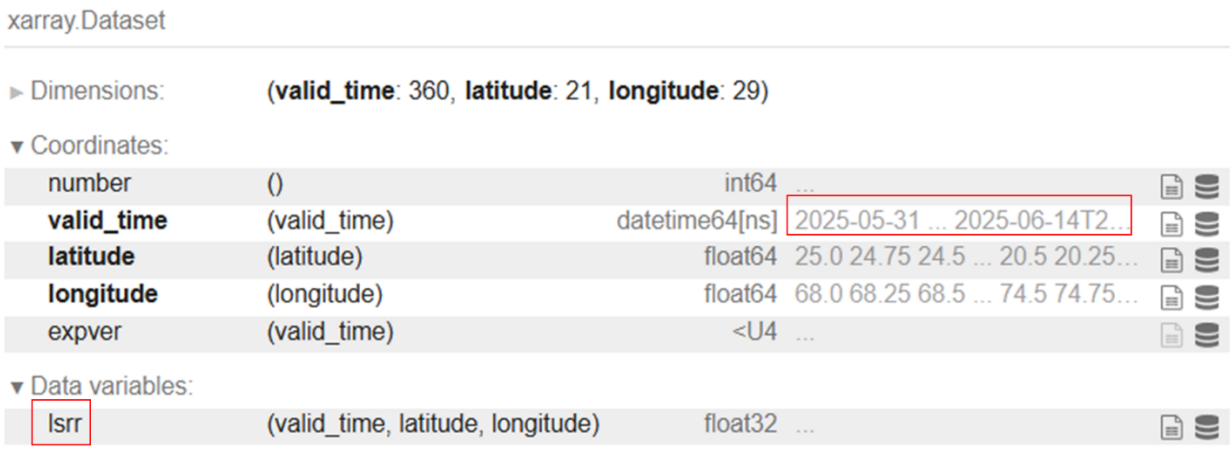


**Figure 5.13 Temp Data Reading**

**Figure 5.14** depicts the spatial distribution of rainfall over Gujarat using NetCDF data. The color scale represents rainfall intensity, with higher values concentrated in the southern coastal region. Most areas show negligible rainfall, while localized precipitation is observed near South Gujarat. This plot highlights the spatial variability of rainfall patterns across the state.

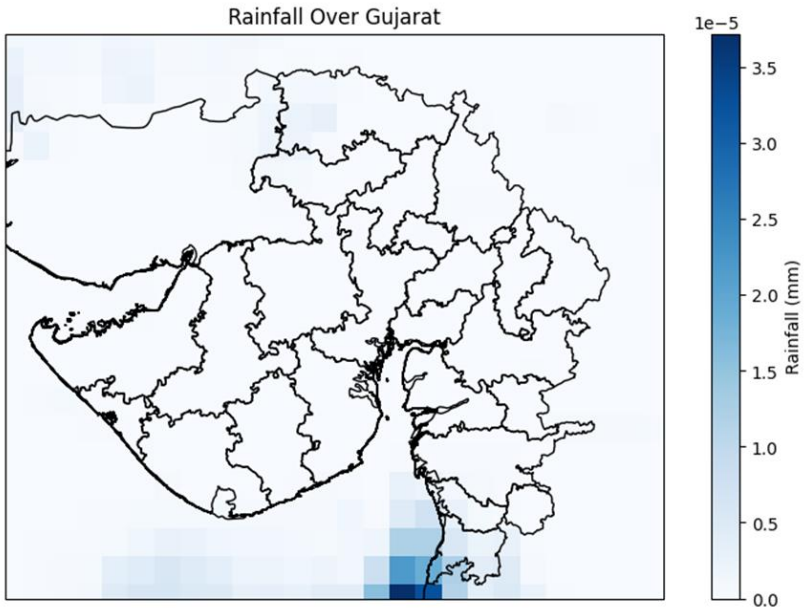


**Figure 5.14 Rain Data Plot**

**Figure 5.15** shows a sample training batch for rainfall prediction over Gujarat. Here, 9 sequential rainfall frames from 5 AM to 1 PM are provided as input to the model. The model then predicts the next frame, representing rainfall at 1-hour ahead. This setup enables the learning of temporal rainfall patterns for short-term forecasting.

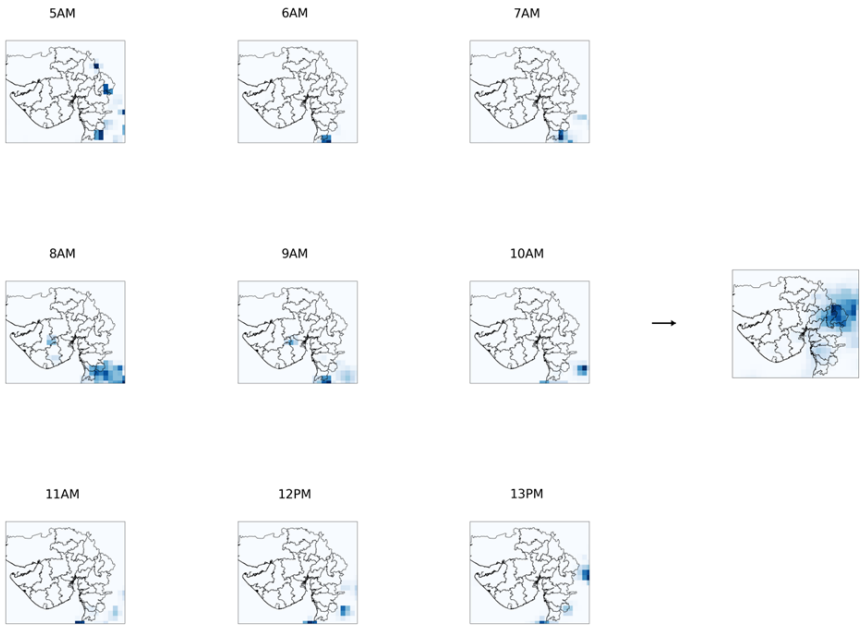


**Figure 5.15 Rain Data Sample Training Batch**

**Figure 5.16** shows the training performance of the rain prediction model. The left plot compares training and validation loss, both decreasing steadily across epochs. The right plot presents training

and validation MSE, indicating improved prediction accuracy as epochs progress. The curves confirm that the model achieves good convergence with minimal overfitting.

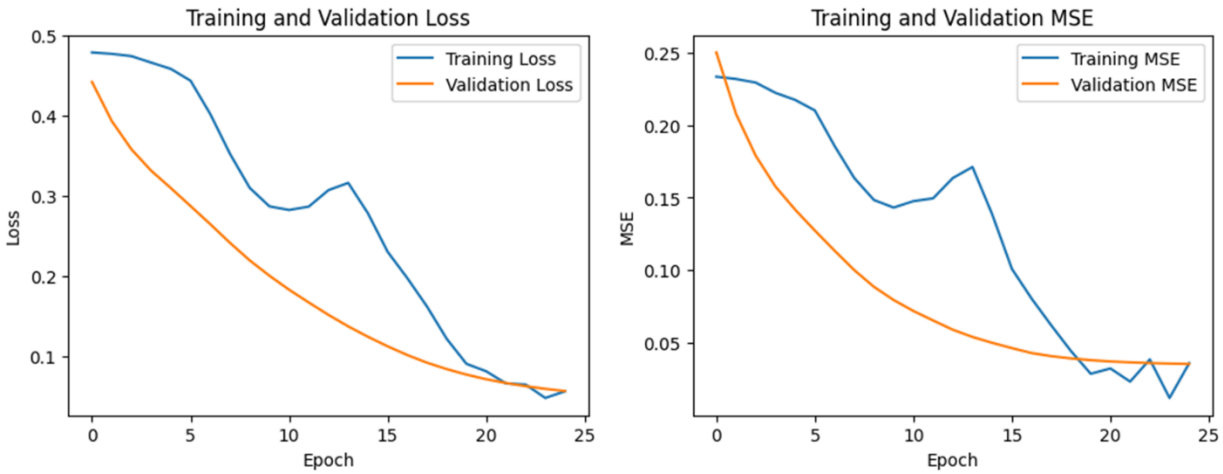


**Figure 5.16 Rain Model Training and Validation**

**Figure 5.17** compares actual and predicted rainfall frames over Gujarat. The top row shows observed rainfall frames on 14th June 2025, while the bottom row shows model predictions. The predicted frames capture the spatial pattern of rainfall events, though with slight intensity differences. This indicates the model's ability to reasonably forecast short-term rainfall distribution.

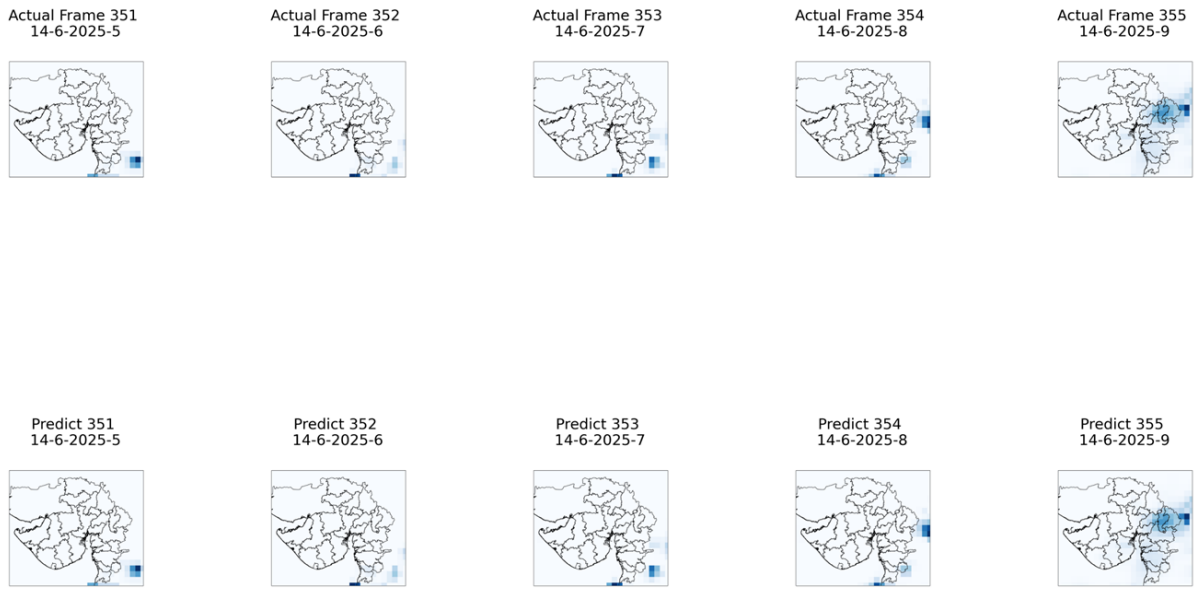


**Figure 5.17 Rain Actual Vs Predicted Frames**

**Table 5.5 Actual Vs Predicted Rain Values**

| Date & Time | Actual Rain (mm) | Predicted Rain (mm) | Accuracy |
|---|---|---|---|
| 14/06/2025:05:00 IST | $1.64 \times 10^{-5}$ | $1.58 \times 10^{-5}$ | 96.34% |
| 14/06/2025:06:00 IST | $1.72 \times 10^{-5}$ | $1.70 \times 10^{-5}$ | 98.84% |
| 14/06/2025:07:00 IST | $1.78 \times 10^{-5}$ | $1.67 \times 10^{-5}$ | 93.82% |
| 14/06/2025:08:00 IST | $1.79 \times 10^{-5}$ | $1.69 \times 10^{-5}$ | 94.41% |
| 14/06/2025:09:00 IST | $1.84 \times 10^{-5}$ | $1.72 \times 10^{-5}$ | 93.48% |

**Table 5.6 Parameters Between Actual Rain Frame Vs Predicted Rain Frame**

| Date & Time | MSE | PSNR | RMSE | SSIM |
|---|---|---|---|---|
| 14/06/2025:05:00 IST | 0.045 | 66.44 | 0.2121 | 0.986 |
| 14/06/2025:06:00 IST | 0.046 | 66.32 | 0.2147 | 0.986 |
| 14/06/2025:07:00 IST | 0.048 | 66.67 | 0.2191 | 0.987 |
| 14/06/2025:08:00 IST | 0.043 | 66.82 | 0.2072 | 0.992 |
| 14/06/2025:09:00 IST | 0.049 | 66.80 | 0.2213 | 0.991 |

## 5.2 Discussion

The analysis of experimental results demonstrates the effectiveness of the proposed 3D-ConvLSTM model compared to 2D-ConvLSTM and existing models. From Table 5.7, it is evident that 3D-ConvLSTM significantly outperforms 2D-ConvLSTM with a much lower MSE (0.042 vs. 12.856) and higher SSIM (0.997 vs. 0.56), indicating superior prediction accuracy and structural similarity. Table 5.8 shows that increasing the number of training days leads to reduced accuracy, as error values rise and SSIM decreases, highlighting an optimal balance at 15 days. Similarly, Table 5.9 reveals that block size plays a crucial role, where a 10-frame block yields the best performance, while smaller or larger blocks degrade results. Finally, the comparative analysis in Table 5.10 confirms that the proposed model achieves the lowest MSE (0.042) and highest SSIM (0.997) among all benchmarked approaches, establishing its robustness and superiority for spatio-temporal prediction tasks.

**Table 5.7 Layer Analysis**

| Layers | Days | Frames | Blocks | MSE | PSNR | RMSE | SSIM |
|---|---|---|---|---|---|---|---|
| 2D-ConvLSTM | 15 | 15 D x 24 H=360 | 360 F /10 [9+1] =36 | 12.856 | 10.22 | 3.586 | 0.56 |
| 3D-ConvLSTM | 15 | 15 D x 24 H=360 | 360 F /10 [9+1] =36 | 0.042 | 66.259 | 0.207 | 0.997 |

**Table 5.8 Day Analysis**

| Layers | Days | Frames | Blocks | MSE | PSNR | RMSE | SSIM |
|---|---|---|---|---|---|---|---|
| 3D-ConvLSTM | 15 | 15 D x 24 H=360 | 360 F /10 [9+1] =36 | 0.042 | 66.259 | 0.207 | 0.997 |
| 3D-ConvLSTM | 30 | 30D x 24H=720 | 720F /10 [9+1]=72 | 0.892 | 22.55 | 0.487 | 0.627 |
| 3D-ConvLSTM | 45 | 45D x 24H=1080 | 1080F /10[9+1]=108 | 1.56 | 15.12 | 0.389 | 0.528 |
| 3D-ConvLSTM | 60 | 60D x 24H=1440 | 1440F /10[9+1]=144 | 2.87 | 12.22 | 0.282 | 0.481 |

**Table 5.9 Block Analysis**

| Layers | Days | Frames | Blocks | MSE | PSNR | RMSE | SSIM |
|---|---|---|---|---|---|---|---|
| 3D-ConvLSTM | 15 | 15 D x 24 H=360 | 360 F /5 [4+1] =72 | 0.892 | 22.55 | 0.487 | 0.627 |
| 3D-ConvLSTM | 15 | 15 D x 24 H=360 | 360 F /10 [9+1] =36 | 0.042 | 66.259 | 0.207 | 0.997 |
| 3D-ConvLSTM | 15 | 15 D x 24 H=360 | 360 F /20 [19+1] =18 | 2.58 | 16.72 | 0.785 | 0.428 |
| 3D-ConvLSTM | 15 | 15 D x 24 H=360 | 360 F /24 [23+1] =15 | 3.12 | 12.22 | 0.654 | 0.325 |

**Table 5.10 Comprative Analysis With Exitsing Models**

| Algorithm Model | Average MSE | Average PSNR | Average RMSE | Average SSIM |
|---|---|---|---|---|
| GWO-nested CEEMDAN-CNN-BiLSTM [15] | 0.064 | 63.295 | 0.2634 | 0.987 |
| Wavelet-LSTM [8] | 0.076 | 61.278 | 0.283 | 0.982 |
| Dual-Optimization Wind Speed Model [3] | 0.082 | 60.567 | 0.295 | 0.980 |
| Seq2Seq with Spatial-Temporal Fusion [4] | 0.095 | 58.234 | 0.312 | 0.976 |
| BERT4ST [13] | 0.071 | 62.834 | 0.272 | 0.984 |
| Proposed Model | 0.042 | 66.259 | 0.207 | 0.997 |

Table 5.10 presents a comparative analysis of the proposed 3D-ConvLSTM model with existing state-of-the-art algorithms. The results clearly indicate that the proposed model achieves the best performance across all evaluation metrics, with the lowest MSE (0.042) and RMSE (0.207), along with the highest PSNR (66.259) and SSIM (0.997). Compared to models such as GWO-nested CEEMDAN-CNN-BiLSTM, Wavelet-LSTM, and Seq2Seq with Spatial-Temporal Fusion, the proposed model shows a substantial improvement in both accuracy and structural preservation of

spatio-temporal features. This demonstrates the capability of the 3D-ConvLSTM approach in capturing complex spatial-temporal dependencies more effectively than traditional deep learning and hybrid models.

In chapter summary, the results and discussion validate the superior performance of the proposed 3D-ConvLSTM model in spatiotemporal weather prediction. The model effectively integrates 3D convolutional operations with LSTM-based temporal learning to capture both fine-grained local variations and large-scale atmospheric dynamics. Experimental findings reveal a significant reduction in error metrics, achieving the lowest MSE (0.042) and RMSE (0.207), alongside the highest PSNR (66.259) and SSIM (0.997). The stability of training and validation curves confirms robust learning with minimal overfitting, while visual comparisons demonstrate the model's ability to replicate real-world weather transitions accurately. Moreover, the framework maintains computational efficiency despite handling multidimensional radar data, making it practical for real-time deployment.

# Chapter 6
# Conclusion and Future Scope

This research introduced a robust and high-fidelity deep learning framework for wind field forecasting, employing a ConvLSTM-based architecture specifically designed to address the challenges of spatiotemporal variability in wind velocity prediction. By training and validating the model on wind velocity data collected from the Gujarat region over a 15-day period, the study demonstrated the effectiveness of the proposed approach in outperforming several state-of-the-art models. The proposed model demonstrates clear superiority over existing approaches, achieving an average MSE of 0.0429, PSNR of 66.2592, RMSE of 0.2071, and SSIM of 0.9978. Compared with state-of-the-art methods such as GWO-nested CEEMDAN-CNN-BiLSTM, Wavelet-LSTM, Dual-Optimization Wind Speed Model, Seq2Seq with Spatial–Temporal Fusion, and BERT4ST, the proposed framework reduces MSE by 34–56%, lowers RMSE by 22–34%, improves PSNR by 6–14%, and enhances SSIM by 1–2%. These percentage gains clearly indicate that the model substantially outperforms existing techniques, delivering more accurate, stable, and reliable weather nowcasting outputs. The integration of ConvLSTM layers with BatchNormalization allowed the network to capture dynamic dependencies while mitigating issues of overfitting and vanishing gradients, enabling it to model both spatial correlations and temporal evolution with high precision. Unlike traditional statistical or numerical weather prediction approaches that often struggle with nonlinear patterns, this work highlights the significant potential of deep learning methods in generating detailed and high-resolution wind field predictions suitable for applications in renewable energy management, aviation safety, and disaster preparedness. Overall, the research establishes ConvLSTM-based architectures as a powerful tool for advancing wind forecasting capabilities and provides a foundation for further innovations in spatiotemporal modeling of atmospheric phenomena.

Future efforts can focus on expanding the dataset to cover longer durations and diverse regions, as well as incorporating multi-source data such as radar and satellite inputs for richer feature representation. Exploring hybrid models with attention mechanisms or transformer-based layers may further improve accuracy, while integrating explainable AI would enhance trust and transparency in practical applications. Finally, extending the approach for real-time deployment

and medium-range forecasting remains an important direction to demonstrate its full operational potential.

# Research Publication

1. Sachin Kanubhai Patel, Sandipkumar Ramanlal Panchal and Sweta S Panchal, “Advanced Learning Techniques for Short-Term Atmospheric Predictions: An Overview”, presented in the Second International Conference on Automation, Computing and Renewable Systems (ICACRS-2023) held during December 11-13, 2023, organized by Mount Zion College of Engineering and Technology, Pudukkottai, Tamil Nadu, India. [indexed in Scopus] DOI: **https://doi.org/10.1109/ICACRS58579.2023.10405022**

2. Sachin Kanubhai Patel, Sandipkumar Ramanlal Panchal and Sweta S Panchal, “Wind Nowcast On Radar Imagery Employing Deep Learning Technique”, published in Journal of Electrical Systems Vol. 20 No. 3 (2024), PP. 7533-7541, Dec. 2024. ISSN: 1112–5209 [indexed in Scopus] DOI: **https://doi.org/10.52783/jes.7493**

3. Sachin Kanubhai Patel, Sandipkumar Ramanlal Panchal and Sweta S Panchal, “High-Fidelity Wind Field Prediction Using Deep Spatiotemporal Learning”, published in Journal of Information Systems Engineering and Management Vol. 10 No. 52s (2025), PP. 758-768, Dec. 2025. ISSN: 2468-4376 [indexed in Scopus] DOI: **https://doi.org/10.52783/jisem.v10i52s.10785**

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